Proceedings of the 2019 Winter Simulation Conference
N. Mustafee, K.-H.G. Bae, S. Lazarova-Molnar, M. Rabe, C. Szabo, P. Haas, and Y.-J. Son, eds.

SIMULATING PROFIT LOSS IN BEHAVIORAL NEWSVENDOR PROBLEMS

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ABSTRACT

The newsvendor problem is one of the classic models in inventory management. Although the optimal order quantity can be calculated, experiments reveal that decision makers often do not select the optimal quantity. These decision biases have been well studied, but analysis of the financial risk associated with these suboptimal decisions is limited. This paper examines the impact on profit by comparing the expected profit of suboptimal decisions with that of optimal decisions. We first conduct a literature review of behavioral results in the newsvendor setting. We use the results reported in the literature to determine parameters in a model for behavioral newsvendor decision making. We then build a Monte Carlo simulation that incorporates the behavioral decision making model, heterogeneity of decision makers, and parameters of the newsvendor decision to calculate the expected profit loss. The simulation results shed light on the financial risk associated with these inventory decisions.

1 INTRODUCTION

The newsvendor problem is one of the classical models in inventory management. It is framed around an inventory decision for a perishable good. The optimal order quantity can be derived mathematically, but experiments reveal that decision makers consistently deviate from the optimal quantity. Schweitzer and Cachon (2000) conduct behavioral experiments and find a systematic pattern in which participants order amounts lower than optimal for high profit products and higher than optimal for low profit products. The authors call this pattern a pull-to-center bias and show it is not well explained by risk attitudes, Prospect Theory, or stock-out aversion. This finding has garnered numerous extensions in the literature examining the factors that contribute to these decisions (e.g., Benzion et al. 2008; Bolton and Katok 2008; Bostian et al. 2008).

While most papers investigate factors contributing to deviations from optimality and descriptions of those deviations, less attention has been given to the economic consequences. This paper addresses this issue by examining the impact of suboptimal ordering decisions on expected profit. We conduct a literature review of behavioral newsvendor experiments and use the results to fit parameters for a model of the average order quantity in an approach consistent with Duggirala et al. (2017). We then build a Monte Carlo simulation model that incorporates this behavioral model, heterogeneity of decision makers, and problem parameters in the calculation of expected profit loss. We use the simulation model to conduct sensitivity analyses to examine how factors such as profit margin and the level of variation in the decision making affect the percentage profit loss, a measure that provides insight to the financial risk associated with these suboptimal decisions.

This work relates to some prior investigations of profit in the newsvendor setting. Mitra (2018) assesses the sensitivity of the expected optimal profit and order quantity to different parameters but does not consider behavioral issues. Khanra et al. (2014) find the newsvendor model is more sensitive to suboptimal decisions than some other models. In one empirical study of managerial decision making in the fashion industry, Fisher and Raman (1996) show that profits increased almost 60% from assisted order decisions relative to the unassisted decisions. Given the potential economic impact, it is necessary to investigate the economic consequences of suboptimal ordering decisions.

The main contribution of this paper is the analysis of financial risk in the form of expected profit loss and expected percentage profit loss associated with suboptimal inventory decisions. The paper is organized as follows. Section 2 presents background information and literature. Section 3 explains the study inclusion criteria and the model of average ordering behavior. Section 4 explains the simulation model, followed by results and discussion in Section 5. Concluding remarks appear in Section 6.

2 BACKGROUND AND LITERATURE

2.1 The Classic Newsvendor Problem

The classic single period newsvendor problem is formulated as follows. A newsvendor must decide the quantity (Q) of a perishable product to order at the beginning of a selling season. (S)he faces a stochastic demand (D) with known distribution function $F(D)$. The cost per unit of the product is c, and the selling price is p. The salvage value is denoted s, and reordering within the time period is not allowed. The unit under-stocking cost is $c_u = p - c$, and unit over-stocking cost is $c_o = c - s$. The cost function of the newsvendor problem can be formulated as

$$C(Q) = c_o(Q-D)^+ + c_u(D-Q)^+. \tag{1}$$

The profit becomes a function of Q, denoted $\pi(Q)$, and can be written

$$\pi(Q) = p\text{Min}(Q,D) - cQ. \tag{2}$$

Then, further calculation shows the optimal order quantity (Q^*) is

$$Q^* = F^{-1}\left(\frac{c_u}{c_o + c_u}\right). \tag{3}$$

We refer readers to Khouja (1999) for the full calculations to reach (3). Details of variations on the problem are available in reviews by Gallego and Moon (1993) and by Petruzzi and Dada (1999).

We call $c_u/(c_o + c_u)$ the critical ratio, which is also defined as the profit margin, $m = c_u/(c_o + c_u)$. If s is 0, then this expression can be simplified to

$$m = \frac{p-c}{p}. \tag{4}$$

If $m \geq 0.5$, the product has a high profit margin, and Q^* is greater than the mean demand. If $m < 0.5$, the product has a low profit margin, and Q^* is lower than the mean demand (Benzion et al. 2008).

2.2 Behavioral Studies of the Newsvendor Problem

The literature shows that both the profit margin and the heterogeneity of decision makers affect the inventory ordering decision. In this section, we present the literature findings related to these topics and later incorporate both the factors into the model and analysis.

Many studies have shown that profit margin affects the pull-to-center bias. However, the results are conflicting on whether the bias is stronger/weaker in high versus low margin conditions. Studies that report a stronger pull-to-center bias in low margin conditions include Schweitzer and Cachon (2000), Benzion et al. (2008), and Bostian et al. (2008). Studies that report a stronger bias in low margin conditions include Ren and Croson (2013) and Rudi and Drake (2014). Other researchers have found that factors such as culture (Feng et al. 2011; Feng and Zhang 2017; Zhao and Zhao 2017) or the way information is presented to participants (Zhang and Siemsen 2019) may modulate the effect of profit margin on decision bias.

Individual heterogeneity is another factor in newsvendor experimental studies. Several studies have shown that individual ordering behavior is highly heterogeneous (Bolton and Katok 2008; Cui et al. 2011; Kremer et al. 2010; Genarneni and Isen 2010; Mortzi et al. 2009; Vericourt et al. 2013; Lau et al. 2014). Thus, it is important to assess the impact of individual heterogeneity on the financial implications.

Several factors have been identified that do not appear to influence the behavioral newsvendor decision. For example, Bolton et al. (2008) show that both managers and students exhibit the pull-to-center bias. Perhaps surprisingly, the demand distribution has been shown to have little impact on the results when comparing demand with a normal versus a uniform distribution (Benzion et al. 2008).

3 MODELING AVERAGE INVENTORY ORDERING BEHAVIOR

3.1 Study Selection

We review the literature of behavioral newsvendor experiments to obtain data to build a model of the average inventory order. Given the potential impact of experimental design on ordering behavior, we define inclusion criteria to identify a set of studies with similar properties. Our focus is on the economic consequences of newsvendors' sub-optimal ordering behavior; thus, we use the search terms "newsvendor", "newsvendor model", "behavioral operations management" and "experiment" through ScienceDirect and Google Scholar to identify relevant studies with laboratory experiments. Next, we eliminate papers or experiments in papers that do not satisfy the inclusion criteria.

Not all the studies identified are appropriate for our analysis. We exclude papers that (i) do not provide the actual order quantities either in aggregated or individual levels, (ii) provide multiple pieces of information that can anchor participants' decisions (e.g., Gavirneni and Xia 2009; Wu and Seidman 2018), (iii) only allow participants to make one decision, and (iv) do not use a symmetric demand distribution (e.g., Kremer et al. 2010).

Each of the studies we included had more than one experiment but not all of the experiments are appropriate for our analysis. Therefore, we selected the experiment(s) of each study according to the following criteria: (i) the experiment provided the actual order quantities, (ii) the experiment had no manipulation of the participants, (iii) the experiment provided participants with instructions on the newsvendor problem, demand distribution and realized demand feedback, (iv) the experiment did not limit the choice set, and (v) the experiment was conducted in the classic newsvendor setting. In addition, some studies consider variables that we do not incorporate in our model and separate participants according to gender, student versus professional, and culture. In these cases, we integrate the data across these variables as a single observation of newsvendor decision making. We do this integration to include another observation while maintaining a greater level of consistency in the experimental design across included observations.

The result of study selection is that 21 papers, encompassing 28 experiments and a total of 81 observations of the average order quantity, are included. Appendix A contains the full list of included papers with additional details on the included experiments. Even after the aforementioned selection process, however, we acknowledge that the data from different papers and studies still vary in the experimental setting, introducing additional variance in the results.

3.2 Model and Fitted Parameters

We use the results from the literature to inform a model of the average inventory ordering behavior. Prior studies use a weighted average of the mean demand and optimal order quantity to represent behavior (Benzion et al. 2008; Bostian et al. 2008). We model behavior consistently with this approach. The parameters are fit using multiple regression to relate the average order quantity $E(Q)$ to $E(D)$ and Q^*,

$$E(Q) = \alpha E(D) + \beta Q^*. \tag{5}$$

The parameters α and β determine how close the order quantity is to $E[D]$ or Q^*. Because the literature shows the profit margin may affect decisions, we fit separate parameters for the low and high margin conditions and use the subscripts L and H, respectively, to denote the margin. (5) is similar to representations of the pull-to-center bias in the literature that use a convex combination of $E[D]$ and Q^* (Bostian et al. 2008; Benzion et al. 2008; Zhang and Siemsen 2019). However, we do not require the parameters sum to one because our interest is in the parameters that best fit the data.

Notably, we define (5) as the prediction of the average inventory ordering behavior. Prior work has found the pull-to-center bias exists in the aggregate data but is not a representation of all decision makers (Bolton and Katok 2008). We therefore use the fitted models of ordering behavior as a representation of the average decision maker and introduce heterogeneity of decision makers in the simulation model.

Including the data from only those studies with low profit margin conditions, the result is

$$E(Q_L) = 0.44E(D) + 0.58Q^*. \tag{6}$$

The $R^2 = 0.9999$ with 36 observations. The p-value for both coefficients are significant (<0.00). If only data from studies with high profit margins are included, the result is

$$E(Q_H) = 0.68E(D) + 0.34Q^*. \tag{7}$$

The $R^2 = 0.99996$ with 45 observations. The p-value for both coefficients are significant (<0.00).

When evaluating the regression analyses for (6) and (7), a few items are worth highlighting. In both cases, the model fit is limited by datasets in which there is a relatively low variance in the values of the predictor variables. This limitation follows from several studies using the same parameters to promote comparability across studies and results in a relative over representation of residuals near zero.

3.3 Simulation Model Formulation

We design a Monte Carlo simulation to calculate the expected impact on profit as a result of suboptimal inventory decisions. First, the parameters of the newsvendor problem are specified, and Q^* is calculated. Then, we assume that different decision makers will make different selections of Q. We assign a distribution $f(Q)$ determined by the mean and variance, but require that the mean of the distribution be determined by (6) or (7), according to the profit margin. We then simulate observations of Q from this distribution. For each observation, we calculate the difference in cost that would have been obtained with Q versus Q^*. Any cost that deviates from the optimal cost can be expressed as a profit loss. Therefore, the expected profit loss, $E[\Delta\pi]$, and the expected percentage profit loss, $pctE[\Delta\pi(Q)]$, are given by

$$E[\Delta\pi] \equiv E[C(Q) - C(Q^*)], \tag{8}$$

$$pctE[\Delta\pi(Q)] = \frac{E[\Delta\pi(Q)]}{E[\pi(Q^*)]} \times 100\%, \tag{9}$$

respectively. Thus, the simulation steps are as follows:

1. Specify the parameters for unit cost, *c*, and the unit price, *p*. The salvage value is set to 0.
2. Specify the demand distribution. We first use a uniform demand distribution that ranges from 0 to 300 and then separately use a normal distribution with $\mu = 150$ and $\sigma = 86.6$.
3. Calculate Q^*.
4. Calculate $E(Q)$ using (6) or (7), depending on the profit margin.
5. Specify the probability density function of *Q,* denoted *f(Q)*, and specify the variance *V* for the distribution.
6. Simulate an inventory ordering decision, *Q*, from *f(Q)*. We use a symmetric triangular distribution.
7. Repeat step 6 for 2000 inventory decisions.
8. Calculate the expected profit loss and the expected percentage profit loss.

The assignment of *f(Q)* represents the heterogeneity of decision makers described by the literature. In the absence of results for each experimental participant, we assign a symmetric triangular distribution to *f(Q)*. This distribution provides a close approximation to the normal distribution (Scherer et al. 2003) and the ability to calculate the minimum and maximum values as a function of the variance, *V,* following $Q_{\min} = \alpha E(D) + \beta Q^* - \sqrt{6V}$ and $Q_{\max} = \alpha E(D) + \beta Q^* + \sqrt{6V}$. We can ensure the range of *Q* is within the range of *f(D)*. This formulation also facilitates a sensitivity analysis to *V*. Although we use *V* as a measure of the diversity of decision makers, it could alternatively represent within subject variation in the case of a single decision maker who behaves inconsistently.

3.4 Analysis

We use the simulation model to examine the effects of behavioral heterogeneity, profit margin, changes in the price, and the demand distribution on the expected profit loss and the expected percentage profit loss.

To examine the effect of heterogeneity among decision makers, we conduct a sensitivity analysis to the variance *V* of decision makers. For the high margin condition, we use parameters $c = 3$ and $p = 12$. For the low margin condition, we use parameters $c = 9$ and $p = 12$. We then vary the value of *V* from 50 to 2,500. The choice of this range is based on the test statistics reported by Schweitzer and Cachon (2000) when determining whether the actual order quantity *Q* differs from Q^*. Given the values of the test statistic, *Q*, Q^*, and the sample size, we calculate the sample variance s^2 from the experiment. We find values of s^2 that range from approximately 779 to 2,336. We use values of *V* in this range, assigning a maximum value of *V* = 2,500 to ensure the range of *Q* is within the range of *f(D)*.

Next, we examine the effect of the profit margin with a sensitivity analysis. We calculate the expected profit loss when $p = 12$ and c varies from 0.1 to 11.9, resulting in profit margins that range from 0.01 to 0.99. We use (6) for all simulations in which the profit margin is less than to 0.5; we use (7) for all simulations in which the profit margin is greater than 0.5. We repeat this sensitivity analysis for $V = 50$ (low heterogeneity), $V = 1000$ (medium heterogeneity), and $V = 2500$ (high heterogeneity).

Changes in the price also affect the expected profit loss when holding the profit margin constant. We examine these effects using $c = 6$ and varying the price from $p = 6$ to 24. We repeat this analysis for $V = 50$ (low heterogeneity), $V = 1000$ (medium heterogeneity), and $V = 2500$ (high heterogeneity).

Finally, we examine the effect of the demand distribution by repeating the profit margin analysis with a normal distribution with the same mean and standard deviation as the uniform distribution.

4 RESULTS AND DISCUSSION

4.1 The Effect of Heterogeneous Decision Makers

We first examine the effect of heterogeneity among the decision makers. The results are presented in Figures 1 and 2. The expected profit loss and the expected percentage profit loss increase as the heterogeneity of decision makers increases. This result occurs because a greater variance among decision makers corresponds to wider range of Q, leading to the existence of inventory decisions that are farther from optimal and instances of greater profit loss.

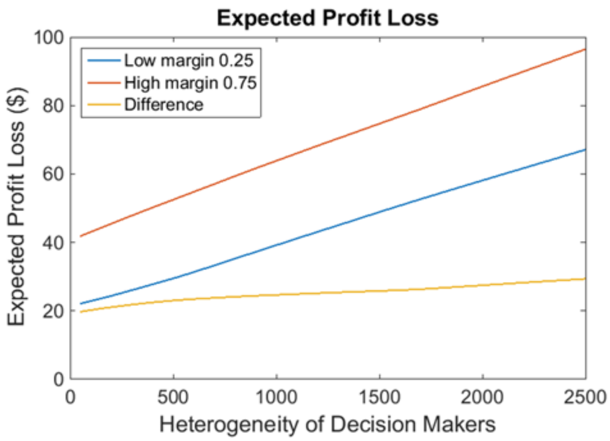

Figure 1: The expected profit loss as the variance in decision makers increases for the low and high margin conditions, with p=12, c=9 (low margin), and c=3 (high margin).

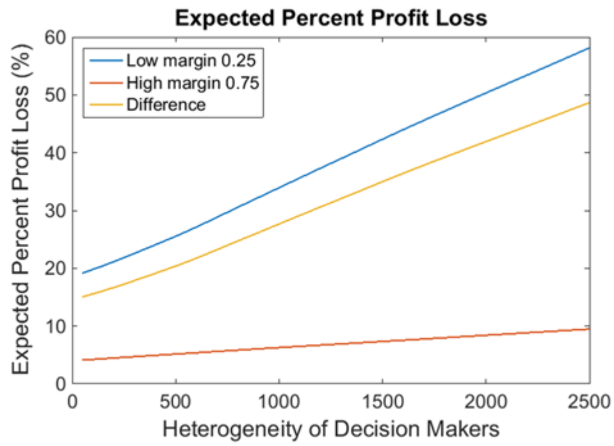

Figure 2: The expected percent profit loss as the variance in decision makers increases for the low and high margin conditions, with p=12 and c=9 (low margin), and c=3 (high margin).

The expected profit loss is greater in the high profit margin condition than in the low-profit margin condition while the percent expected profit loss in low-profit condition is greater than that in high-profit condition. The greater expected profit loss in the high margin case follows from the observation that when each unit has a high potential profit, small changes in the inventory quantity have a correspondingly high impact on the profit. However, this result suggests that although the dollar losses may be greater in high margin cases, suboptimal inventory decisions in low margin conditions may have a greater relative impact on the financial performance because the profit loss represents a greater percentage loss.

The difference in the expected loss between the high- and low-profit conditions increases slightly as the heterogeneity of decision makers increases. The increase in the difference highlights that the expected profit loss increases at a different rate in the two profit margin conditions. The difference also shows some curvature, indicating that although the expected profit loss appears almost linear with increases in the variance of inventory decisions, they are not perfectly linear.

The difference in the expected percentage loss between the two profit margin conditions shows a steep increase as the variance of decision makers increases. This result follows because expected percent profit loss is much more sensitive to changes in the variance in the low-profit margin condition than in the high margin condition. Increases in the variance have a greater relative effect in low margin conditions.

4.2 The Effect of Profit Margin

Next, we examine the effect of the profit margin, $m=(p-c)/p$, on the profit loss. In high margin conditions (i.e. $m>0.5$), Q^* is greater than $E(D)$. In low margin conditions (i.e. $m<0.5$), Q^* is less than $E(D)$. When the profit margin equals 0.5, Q^* equals $E(D)$. The results are presented in Figures 3 and 4.

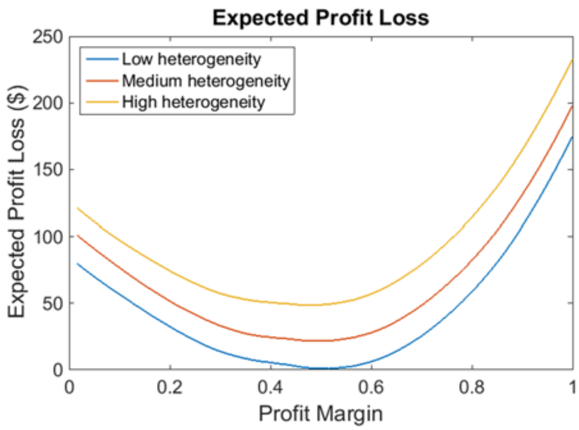

Figure 3: The expected profit loss as the profit margin changes, with p=12 and the cost varying 0.01 to 11.99.

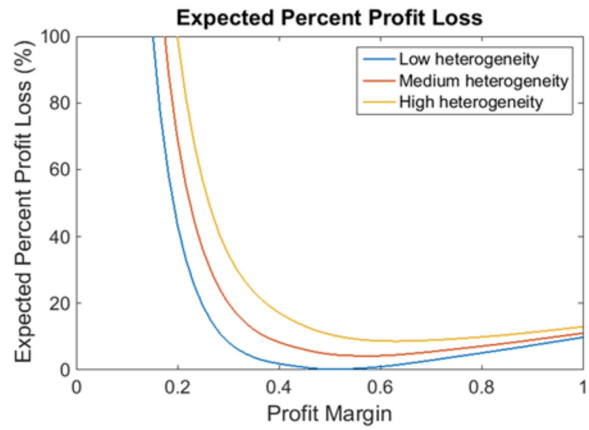

Figure 4: The expected percent profit loss as the profit margin changes, with p=12 and the cost varying from 0.01 to 11.99.

The results show that the minimum expected profit loss and the minimum percent expected profit loss occur near $m = 0.5$. This result is explained by the fact that at $m = 0.5$, *E(D)* equals *Q**, and the decision bias predicted by the pull-to-center effect, and by equations (6) and (7), disappears. However, the expected profit loss and the expected percentage profit loss only approach zero for the low heterogeneity (low variance) case. In cases of greater heterogeneity, a greater number of decision makers select quantities that are farther away from the average value, leading to a nonzero profit loss.

The existence of minima on the curves indicates that there is an optimal profit margin that will result in a reduced effect of suboptimal ordering decisions on financial performance. Interestingly, the profit margin at which the minimum occurs changes as the heterogeneity of decision makers increases. Thus, the profit margin that minimizes the risk of suboptimal decisions depends on both the variance in decisions as well as the profit margin condition. Further, the profit margin that minimizes the expected profit loss decreases as the heterogeneity of decision makers increases, whereas the profit margin that minimizes the expected percentage profit loss increases as the heterogeneity increases.

We also observe different magnitudes of the expected percentage profit losses in low and high margins. The expected percentage profit loss increases dramatically as the margin decreases slightly in a low margin condition. Although the vertical axis in Figure 4 ends at 100%, the expected percentage loss exceeds 200% before the profit margin crosses 0.1. On the other hand, the expected percentage profit loss is relatively flat in the high margin condition. If a newsvendor can perceive this difference, then (s)he might behave differently in low and high margin conditions.

4.3 The Effect of Changes in Price

We also consider the effect of price separately from the profit margin because changes in the profit are a function of changes in the magnitude of the cost and the magnitude of the price in addition to the profit margin. There may also be instances when a firm has a fixed cost but can modify the price.

The results are presented in Figures 5 and 6. We see similar curves as in Figures 3 and 4, showing similar patterns of behavior for the profit loss. Not surprisingly, the expected profit loss decreases when the price approaches 12, the level at which $m = 0.5$ and *E(D)* equals *Q**. That is, the expected profit loss is minimized when the newsvendor orders around the optimal order quantity. The magnitude of the expected profit loss is again greater for higher prices, but the expected percentage profit loss is much greater in the low margin setting than in the high margin setting. The price that minimizes the expected profit loss decreases as the heterogeneity (variance) of decision makers increases, while the price that minimizes the expected percentage profit loss increases with heterogeneity.

Figure 5: The expected profit loss as the profit margin changes, with *c*=*6* and the price varying 6 to 24.

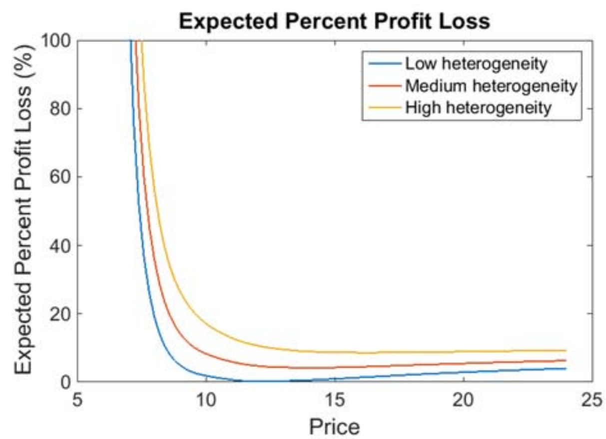

Figure 6: The expected percent profit loss as the profit margin changes, with *c*=6 and the price varying from 6 to 24.

There may also be scenarios in which market conditions do not support changes in the price, but a firm could modify its costs. In this case, the results for changes in cost would largely mirror the results in Figures 5 and 6, with the observations occurring at low(high) prices occurring instead at high(low) costs.

4.4 Sensitivity to the Demand Distribution

Finally, we examine how sensitive the results are to the shape of the demand distribution by repeating the simulation when the demand follows a normal distribution with a mean and standard deviation equal to those of the uniform distribution used previously. We compare how the expected profit loss and the expected percentage profit loss change with the profit margin for each demand distribution. The results are shown in Figures 7 and 8.

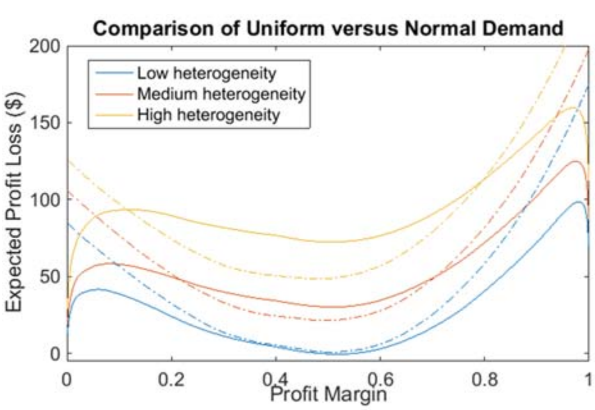

Figure 7: The expected profit loss when demand follows a normal distribution (solid lines) and a uniform distribution (dotted lines).

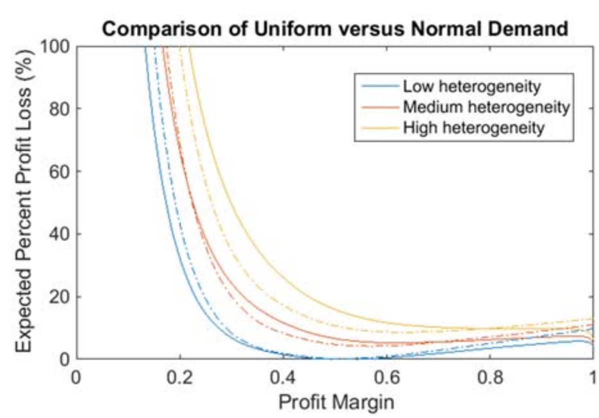

Figure 8: The expected percent profit loss when demand follows a normal distribution (solid) lines) and a uniform distribution (dotted lines).

Three notable patterns emerge. First, the effect of the distribution is minimized near $m = 0.5$, which is expected as this is the point at which the effect of suboptimal decisions in general is minimized. Second, the effect of the distribution is minimized when the heterogeneity of decision makers is smallest, with very little difference shown in the expected percentage profit loss in the low heterogeneity case. Third, when a moderate amount of variance in decision making exists, uniform demand results in a lower expected profit loss near $m = 0.5$, but results in greater expected profit loss near the extreme margins of $m = 0$ and $m = 1$ relative to normally distributed demand. These findings further underscore the importance of understanding the heterogeneity of decision makers to obtain an accurate estimate of the financial risk associated with suboptimal decisions.

5 CONCLUSION

In this paper, we use data from the literature of behavioral newsvendor experiments to calculate parameters for a model to predict the average ordering behavior of suboptimal decision makers. We use this model as an input to a simulation that calculates the financial impact of suboptimal inventory decisions. The simulation is used to examine how changes in the heterogeneity of decision makers, the profit margin, the unit price, and demand distribution changes affect the financial risk associated with these decisions.

The results suggest several implications for organizations. Although the absolute dollar value of the financial impact of suboptimal decisions is greater in a high margin setting, organizations with low margin products may feel a greater financial impact from suboptimal decisions because the profit loss represents a greater percentage loss. We also show that a profit margin exists such that the impact of suboptimal decisions is minimized, but the minimum depends on the heterogeneity of decisions in the organization in addition to the profit margin, unit price, and unit cost. These findings suggest that organizations may wish to consider how inventory ordering decisions are made, and the potential for suboptimal ordering, as a consideration when calculating the optimal price for a product. We also show these patterns of behavior for the expected profit loss and the expected percentage profit loss with respect to changes in the profit margin are similar when demand follows a uniform distribution or a normal distribution.

Because numerous variations on the newsvendor problem exist, many directions of future research are possible. For example, we have made the assumption that the demand distribution is known to show the effect in the best case scenario, but in practice, there may be uncertainty about the demand distribution. Other complications such as demand seasonality or demand chasing by decision makers may also exist and could be incorporated to provide further insight to the financial risk associated with these decisions.

ACKNOWLEDGMENTS

This work was generously supported by a Research Award from the University of Missouri-St. Louis.

A APPENDIX

Table 1: Summary of papers included in the behavioral model of ordering behavior with details about the included and excluded experiments within each paper.

Reference	No. Decisions	Demand Distribution	Profit Margin	Treatments	Order Quantity	Inclusion
Schweitzer and Cachon (2000)	15	U(1,300)	0.75, 0.25	none	given	yes
		U(1,300), U(901,1200)	0.75, 0.25	demand range	given	yes
Bolton and Katok (2008)	100	U(1,100), U(51,150)	0.75, 0.25	learning	given	yes
				limited order options	given	no
				foregone payoff feedback	given	yes
				order frequency	given	no
Benzion et al. (2008)	100	U(1,300), N(150,50)	0.75, 0.25	distribution effect	given	yes

Bostian et al. (2008)	30	U(1,100)	0.75, 0.5, 0.25	none	given	yes
			0.75, 0.25	double payoff	given	yes
			0.75, 0.5, 0.25	order & feedback frequency	given	no
Lurie and Swaminathan (2009)	30	U(1,1000), U(450,550)	0.75	none	given	yes
	3,5,6,10	U(1,1000), U(450,550)	0.75	feedback frequency	given	no
	3,6,30	U(1,1000)	0.75, 0.25	change penalty	given	no
Feng et al. (2011)	100	U(1,100), U(51,150)	0.75, 0.25	cultural difference	given	yes
			0.75, 0.25	limited order options	given	no
Vericourt et al. (2013)	20	U(1,100), U(51,150)	0.75, 0.25	gender difference	given	yes
	60	U(1,100), U(51,150)	0.75, 0.25	measured financial risk	given	yes
Moritz et al. (2013)	12, 25	N(100,20), N(100,30)	0.83, 0.75, 0.5, 0.25	individual difference	given	yes
Ren and Croson (2013)	50	N(100,30)	0.75, 0.25	test overconfidence	given	yes
			0.75, 0.25	manipulate overconfidence	given	no
Schiffels et al. (2014)	30	U(1,100)	0.75, 0.5, 0.25	none	given	yes
				penalty cost	given	no
Rudi and Drake (2014)	50	N(1000,400)	0.75, 0.25	demand feedback	given	yes
Ockenfels and Selten (2014)	200	U(0,100)	0 - 1 (0.1+)	impulse balance equilibrium	given	yes
Kaki et al. (2015)	15	U(0,300)	0.75, 0.25	none	given	yes
				supply uncertainty	given	no
Kocabiyikoglu et al. (2015)	40	U(0,80), U(10,70), U(20, 60), U(30, 50)	0.75, 0.25	none	given	yes
				revenue management	given	no
Lee and Siemsen (2016)	20	N(5000,400)	0.92, 0.75, 0.58, 0.25	none	given	yes
	20	N(5000,400)	0.92, 0.75, 0.58, 0.25	task decomposition (indirect order)	given	no
	30	N(5000,1600)	0.75, 0.25	decision support system	given	no
Feng and Zhang (2017)	50	U(0,100)	0.75, 0.25	single newsvendor	given	yes
				competing newsvendors	given	no
Zhao and Zhao (2017)	30	U(1,50)	0.75, 0.25	single newsvendor	given	yes
	60	U(1,100)	0.75, 0.25	competing newsvendors	given	no
Zhao et al. (2016)	60	N(600,100)	0.75, 0.25	uncensored demand	given	yes
		not given	0.75, 0.25	censored demand	given	no
Schultz et al. (2017)	20	U(50,150)	0.7, 0.3	framing	given	yes

Lee et al. (2018)	100	U(1,100), U(51,150)	0.75, 0.25	learning	given	yes
				limited order options	given	no
				foregone payoff feedback	given	yes
				order frequency	given	no
	15, 20	not given	none	procurement auction	given	no
Zhang and Siemsen (2019)	40	U(1,100)	0.75, 0.25	none	given	yes
				salience of underage cost	given	yes
				likelihood of loss	given	yes
				decision support system	given	no

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